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Contents

Explaining the occupational structure of Dutch sectors of industry, 1988-2003*

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Abstract

We develop a new model to explain the occupational structure of Dutch sectors of industry. The non-homothetic production function we use takes account of capital-skill complementarities, skill-biased technological change and the interaction between labour demand and supply.

We estimate the structural parameters of the model for the period between 1988 and 2003 using system dynamic OLS techniques to account for the employment dynamic dependence across occupations and sectors of industry. The employment series by occupation and sector have both a long run and a short-run relationship with value added, capital and R&D. The short run dynamics can further be decomposed into intra and intersectoral dynamics.

We find that both the long run and short run relationships explain a significant part of employment by occupation and sector of industry. Moreover, employment by occupation and sector is significantly affected by both the intra- and intersectoral dynamics.

JEL Classification: J21, J23.
Keywords: Labour demand, Occupational structure, Skill-biased technological change, Capital-skill complementarity.

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1 Introduction

The occupational structure of the economy varies a great deal across sectors and over time. Across sectors, the occupational structure shows large differences between firms even in narrowly defined industries (see Baily et al. 1992, Olley and Pakes 1996 and Abowd et al. 1999). This tremendous heterogeneity in employment composition across economic sectors seems to be consistent with a conjecture that the modes of production vary a great deal between firms in different sectors (see Idson and Oi 1999, and Bayard and Troske 1999). The shape of the production function and in particular the ease to substitute between the various inputs of production, between capital and skill-groups of workers and between occupational groups of workers, is found to be a prominent explanatory factor of differentials in employment composition across industries (see Dupuy and de Grip 2005).

In this paper we analyze changes in the occupational structure of the various sectors of industry in the Netherlands. The output of each sector is produced using a non-homothetic production function. Although each sector of industry uses the same *type* of production function, the technology parameters of these functions may vary across sectors and take into account capital-skill complementarities, skill-biased technological change and the interaction between labour demand and supply. Capital-skill complementarity implies that the employment of high-skill occupations within industries grows faster than the employment of other occupations due to the capital deepening of production. In particular high-tech capital usage seems to be responsible for the rising employment share of non-production workers in sectors of industry. The results of several empirical studies confirm the employment shift to these relatively highly-skilled workers due to skill biased technological change (e.g. Berman, Bound and Griliches 1994; Machin and Van Reenen 1998).

We estimate the structural parameters of the model for the period between 1988 and 2003 using system dynamics OLS techniques to account for the employment dynamics dependence across occupations and sectors of industry. The employment series by occupation and sector have both a long run relationship with levels of value added, capital and R&D, reflecting the production technology specific to each sector, and a short-run relationship with changes in value added, capital and R&D. The short run dynamics can further be decomposed into intra and intersectoral dynamics. The intrasectoral dynamics indicates that changes in the explanatory variables in a sector affect occupational employment in that sector whereas the intersectoral dynamics indicates that changes in the explanatory variables in a sector affect occupational employment in other sectors. We find that both the long run and short run relationships explain a significant part of employment by occupation and sector of industry. Moreover, employment by occupation and sector is significantly affected by both the intra- and intersectoral dynamics.

Most studies up to now do differentiate between white-collar and blue-collar occupations or non-production and production workers, which are typically labeled as skilled and unskilled labour, respectively. However, Osburn (2001) analyses the employment shifts of detailed occupations within U.S. manufacturing industries. She shows that in general the increased usage of capital and technology is the driving force behind the occupational upgrading within sectors of industry. The increase of the relative demand for highly-skilled workers is due to capital-skill complementarities and skill biased technological change. We are particularly interested whether these complementarities hold for the whole labour market or differ between the agricultural, manufacturing, commercial or public sectors of industry. Moreover, Osburn shows that for some selected occupations the empirical results are puzzling. For example, she finds opposite effects to those expected for the computer engineers. Therefore it is useful to analyze the impact of investments in capital and technology for the whole spectrum of occupations and sectors of industry. We will estimate our model by using data on the occupational structure within sectors of industry of the Dutch labour market between 1988 and 2003. The occupations are clustered in 44 occupational classes, which are compatible with the 3-digit level of the International Standard Classification of Occupations (ISCO).

In this paper, we will point at the economic significance of four explanatory factors for the employment level of occupational classes within economic sectors by developing a new model of occupational structure. We argue that the changes over time of the employment levels of occupations within economic sectors occur because of: (1) changes in the level of production, (2) changes in capital intensity within sectors, (3) technological change and its skill-biased nature and (4) relative wages of occupational groups of workers affecting relative demand and supply forces.

We first account for changes in occupational employment due to exogenous changes in the level of production. Changes in the output level are achieved by changes in the quantity of input used. As long as the mode of production satisfies certain conditions (Homogenous-Homothetic of degree one), the same input mix is optimal to produce all possible levels of output. However, under a general less restrictive functional form (non-homothetic), each output level has a different optimal input mix. Under this more general mode of production (see for instance Dick and Medoff 1975), changes in output have consequences in terms of the occupational composition of employment in each sector of activity.

The second source of changes in occupational employment is the changes in capital intensity. Most studies investigating the shape of the production function show empirical regularities about the degree of complementarity and substitution of the various occupational groups of workers and capital input (see Hamermesh 1986, 1993). Most often, white collar workers and capital are found to be quantity complements while blue collar workers and capital are usually quantity substitutes. The quantity of white collar workers needed increases as the capital intensity increases, whereas the quantity of blue collar decreases with an increase of the capital intensity. Therefore, exogenous shocks that shifts the capital intensity out of its long run equilibrium level induce changes in the occupational employment via the substitution mechanism. When the level of capital is intensified, the mode of production requires more white collar workers as the two inputs are quantity complements. However, blue collar workers are replaced in the production process by the capital input as the degree of quantity substitutability between both inputs indicates. Shifts in the level of capital alter the occupational structure within an economic sector via the substitution possibilities enabled by the mode of production specific to this economic sector.

The third factor of changes in occupational structure is Skill-Biased Technological Change (SBTC) and/or changes in skill requirements. New technologies such as computers may require skills that are more expensive to acquire than existing skills and since it is less costly for skilled-workers to acquire these new skills, skilled-workers are the first to use the new technology. This raises their marginal productivity and induces substitution between groups of workers (see Dunne et al. 2000). However, evidence for the market value of the skills associated to the new technologies and therefore evidence for the existence of new skills is questioned by some authors (see DiNardo and Pischke 1997). Yet, new technologies may affect the occupational structure simply because some workers have certain, already existing, skills that enable them to make more effective use of a computer. The workers endowed with those skills will be the first to be assigned a computer. This would raise the productivity of workers in jobs that are computerised and therefore shift the skill requirements for these jobs and the occupational structure as a result of the diminishing importance of routine tasks.

Independent of the eventual requirement of new specific skills by technological progress, skill-biased technological change or changes in skill requirements result into similar non-neutral changes regarding the shape of the production function within industries. The magnitude of the non-neutral factor-augmenting technological development results in changes in the occupational structure of employment over time. Moreover, as changes in the technological parameters and the elasticities of substitution differ significantly across industries, it can be expected that the occupational structure and labour demand by occupation will show very different developments.

The fourth factor of changes in the occupational structure is the interaction between labour demand and supply. Shifts in the supply in the various occupational segments of the labour market lead to wage adjustments in order to bring about equilibrium. These shifts in the relative wage rates induce adjustment in the occupational composition within each industry as the relative marginal productivity of the various groups of workers shifts.

Section 2 presents the theoretical model of occupational structure. Section 3 discusses the data and the results of the required econometric tests to estimate the model. Section 4 presents some ex post predictions and the results of the estimated parameters for 43 occupational classes and 13 sectors of industry. Section 5 concludes the paper.

2 A theoretical model of occupational structure

The economy

In this paper, each sector i is assumed to produce a physical output, Y_{it}, in time period t. For the sake of convenience and without loss of generality, the output price in each sector, p_{it} is used as a common denominator to all input prices of the associated sector. The production function that relates input quantities to output level is different across sectors. Each sector may use different inputs of labour, some economic sectors have specific occupations that are not represented in other sectors of the economy, but all use a capital input.[1] Labour inputs are differentiated by occupational segments and measured in number of workers. The labour market and the commodity(-ies) markets are assumed to be perfectly competitive.

The production function in sector i at time t with inputs characterized by capital K and J occupational segments is given by:

$$Y_{it} \equiv F_i \left(K_{it}, L_{i1t}, ..., L_{iJt}\right) = \left(a_{iK} K_{it}^{\beta_{iK}} + \sum_j a_{ij} L_{ijt}^{\beta_{ij}}\right)^{1/\beta_i} \qquad (1)$$

with $\beta_{iK}, \beta_{ij} > 0 \ \forall i, j$ and $\beta_i > 0 \ \forall i$, $a_{iK} + \sum_j a_{ij} = 1$ and $a_{iK}, a_{ij} > 0 \ \forall i, j$ and where a_{iK} and a_{ij} are the respective efficiency parameters of capital input and workers in occupation j in sector i. The β's, and are technology parameters upon which the elasticities of substitution between the various inputs depend. K_{it} is the capital input in industry i in period t and L_{ijt} the number of workers in occupation j in sector i in period t.

The function depicted above has the direct addilog form (see Dick and Medoff 1975, Gorman 1965, Houthakker 1960, and Mukerji 1963). The function is homogenous of degree $\beta_i/\overline{\beta}_i$ when all technological parameters are equal, $\beta_{iK} = \beta_{ij} = \overline{\beta}_i$ for all i, j and it degenerates to a homogenous of degree 1 CES production function (see Sato 1967) for $\beta_i = \overline{\beta}_i$.

Assuming firms in each sector seek to minimize costs given a certain output level, we derive the following marginal productivity for each input.

[1] Though capital usually consists of very different parts, i.e. machinery, materials, computers etc., we use a one dimensional variable to represent capital due to the lack of more differentiated data.

$$m_{ijt} \equiv \frac{\partial F_i}{\partial L_{ijt}} = a_{ij}\frac{\beta_{ij}}{\beta_i} L_{ijt}^{\beta_{ij}-1} Y_{it}^{1-\beta_i} \quad (2)$$

$$m_{ikt} \equiv \frac{\partial F_i}{\partial K_{it}} = a_{iK}\frac{\beta_{iK}}{\beta_i} K_{it}^{\beta_{iK}-1} Y_{it}^{1-\beta_i} \quad (3)$$

where m_{ikt} and m_{ijt} are the marginal productivity of capital and workers in occupation j respectively, in sector i in time period t.

Rearranging and expressed in logarithm form this gives the demand for the various inputs as a function of the marginal productivity (equal to wage rates and capital price under perfect competition) of the respective inputs, output level and efficiency and technological parameters.

$$l_{ijt} \equiv \ln L_{ijt} = \sigma_{ij}\left(\ln a_{ij} + \ln \beta_{ij} - \ln \beta_i\right) - \sigma_{ij} \ln m_{ijt} + \frac{\sigma_{ij}}{\sigma_i} \ln Y_{it} \quad (4)$$

$$k_{it} \equiv \ln K_{it} = \sigma_{iK}\left(\ln a_{iK} + \ln \beta_{iK} - \ln \beta_i\right) - \sigma_{iK} \ln m_{iKt} + \frac{\sigma_{iK}}{\sigma_i} \ln Y_{it} \quad (5)$$

where $\sigma_{iK} = \frac{1}{1-\beta_{iK}}$, $\sigma_{ij} = \frac{1}{1-\beta_{ij}}$ and $\sigma_i = \frac{1}{1-\beta_i}$.

The long run demand for workers in occupation j within sector i relative to capital therefore reads as:

$$\begin{aligned} l_{ijt} - k_{it} = {} & \frac{\sigma_{ij} - \sigma_{iK}}{\sigma_i} \ln Y_{it} - \\ & \sigma_{iK}\left(\ln a_{iK} + \ln \beta_{iK}\right) - \ln \beta_i \left(\sigma_{ij} - \sigma_{iK}\right) + \sigma_{iK} \ln m_{iKt} + \\ & \sigma_{ij}\left(\ln a_{ij} + \ln \beta_{ij}\right) - \sigma_{ij} \ln m_{ijt} \end{aligned} \quad (6)$$

Isolating separate factors of changes in occupational composition by sector

Economic theory tells us that as long as the production function F_i, that relates input quantities to output, is homothetic, the optimal input mix (relative quantities of input) is invariant of the output level chosen. In that case the production is homogenous of degree one. Therefore, a 1% increase in output requires the same increase of each input. The industry aggregate demand for labour changes in response to output increase, but the mix is invariant.

However, in this paper we will allow the input mix to vary across industries and over time. Changes in the occupational employment composition are caused by exogenous employment shifts between sectors and changes in the occupational structure within a sector. As we described above, these shifts might be driven by labour demand or supply shifts. Demand shifts are characterized by changing modes of production or production technologies altering the distribution of marginal productivity. Moreover, since we assume a non-homothetic production function, a shift in output will alter the optimal input mix. Shifts in investment alter the long-run capital-labour ratio since, skilled workers are a quantity complement with capital while unskilled workers are a quantity substitute. Hence, shifts in the level of capital induce shifts in the occupational composition within industries. Supply shifts, exogenous to our model, are characterized by shifts in the relative wage rates and the capital price, altering the relative marginal productivity of the various inputs of production and therefore also altering the occupational composition within industries. Furthermore, we note that the a_{iK} and a_{ij} parameters may as well depend on time and indicates SBTC or non-neutral factor augmenting.

From our structural long run demand equation, changes in the demand for workers in occupation j in industry i relative to changes in the capital stock can be decomposed as follows:

$$\begin{aligned} \Delta l_{ijt} - \Delta k_{it} &= \frac{\sigma_{ij} - \sigma_{iK}}{\sigma_i} \Delta \ln Y_{it} + \sigma_{iK} \left(\Delta \ln m_{ikt} - \Delta \ln a_{iKt} \right) + \\ & \sigma_{ij} \Delta \ln a_{ijt} - \sigma_{ij} \Delta \ln m_{ijt} \end{aligned} \tag{7}$$

The four terms on the right hand side of equation (7) capture the four factors of changes in the occupational demand for workers in each sector.

1. The first term arises if the production function is not homothetic. This implies that each output level corresponds to a different optimal input mix.

2. The second term captures changes in the demand for capital, which arise from changes in technology $\Delta \ln a_{iKt}$ or changes in the rental price of capital through $\Delta \ln m_{ikt}$. Changes in the capital input induce changes in the relative proportion of inputs which induces substitution between labour input pairs and results into a different occupational mix.

3. The third term captures changes in the relative efficiency of each type of labour via changes in efficiency parameters.

4. The last term captures changes in the relative wages. An increase in the relative wage of workers in occupation j induces an increase in the relative marginal productivity, m_{ijt} which induce substitution between labour input pairs.

3 Quantitative Methodology

3.1 Data

We use employment data on occupations and sectors of industry that have been drawn from the Labour Force Survey (LFS) of Statistics Netherlands. The Dutch LFS is a continuous sample survey research of all people residing in the Netherlands with the exception of residents in institutions, resident care hostels and homes. Each year some 100,000 questionnaires are completed. All people carrying out at least 12 hours paid work per week are allocated to the working population. In this paper, we cover the whole spectrum of occupations and sectors of industry of the labour markert in the Netherlands.

We distinguish between 13 sectors of industry, which are shown in Figure 7. Moreover, we constructed a time series of occupational employment by industry for the period between 1988 and 2003. We distinguish between 43 occupational classes, which are compatible with the International Standard Classification of Occupations (ISCO). These occupational classes are shown in Figure 8. In this paper occupational employment is estimated for 195 combinations of industry and occupation. In the remaining combinations too few workers were employed to construct reliable times series.

The industrial data on value added, wage sum and capital investments (both machinery and structures) are based on the National Accounts of Statistics Netherlands. These time series have a break from 1994 to 1995 due to the introduction of a new system of national accounts. Time series on investments in research and development (definition according to the Frascati Manual of the OECD) are published by Statistics Netherlands. These data are mainly based on R&D and innovation surveys among businesses, research institutes and universities. The industrial data can be downloaded from the website of Statistics Netherlands (www.cbs.nl).

To calculate stocks of capital and R&D we applied the widely used Perpetual Inventory Method (PIM). Time series of investments in capital and R&D are used for the period of 1970-2003, with a depreciation rate of 0.08 and 0.15 respectively. The initial stock of capital and R&D is calculated as the value of investment in the first year divided by the deprecation rate plus the growth rate of investment in the first three years of the time series.

3.2 Econometric model

The econometric model for the occupational employment composition of a sector can straightforwardly be derived from the economic model of Section 2.

$$l_{it} = \underline{x}'_{it}\underline{\gamma}_i + \varepsilon_{it} \tag{8}$$

where l_{it} is log employment in equation i (a combination of industry and occupational code), $\underline{x}_{it}$ is a $k \times 1$ vector of explanatory variables for equation i that contains a constant, a time trend, log capital, log R&D and log value added. ε_{it} is an error term, $\underline{\gamma}_i$ is a $k \times 1$ vector of parameters for the i^{th} occupation$\times$industry equation.

The model as presented in equation 8 represents the long run relationship between employment and R&D, value added[2] and capital. Our empirical objective is to derive consistent estimates of the long run relationship presented in Equation 8. However, as indicated in Table 1, the Augmented Dickey-Fuller (ADF) test statistics (with drift) are not significant for most time series at hand, that is the log employment by occupation and sector as well as the explanatory variables by sector. The empirical testing reveals that all time series on R&D, capital and value added are integrated of order 1. For the employment series by occupation and sector, 172 out of the 195 series are integrated of order 1. This indicates that OLS estimates may be superconsistent reflecting spurious correlation rather than a structural long run relationship.

<insert Table 1>

Since the explanatory variables and employment series are integrated of the same order (1) we need to (and can) test for the cointegration of the series. We proceed to a ADF test of cointegration in the long run relationship (equation 8). The results reported in Table 1 indicate that for 185 out of 195 (95%) occupation-sector combinations, the deviations of the employment series from their long run paths are stationary. The model is therefore characterized by the following cointegration regression for each equation i:

$$l_{it} = \underline{x}'_{it}\underline{\gamma}_i + \varepsilon_{it} \qquad (8)$$

$$\Delta \underline{x}_{it} = \underline{e}_{it} \qquad (9)$$

where $\underline{e}_{it}$ is a $1 \times k$ vector.

Hence, the demand for workers in equation i depicted by the long run relationship in equation 8 could be sensibly estimated by estimation of a $ARDL(1,1)$ model as follows:

$$l_{it} = \underline{x}'_{it}\underline{\gamma}_i + l'_{it-1}\alpha_i + \underline{x}'_{it-1}\underline{\lambda}_i + \varepsilon_{it} \qquad (10)$$

[2]Because of high multicollinearity between the wage sum and value added at the sector level, we drop the wage sum of the equation. Value added therefore captures a global effect of demand shifts due to (1) changes in the output level and (4) changes in the relative wages.

A shortcoming of the estimates of equation 10 based on $ARDL(1,1)$ is that the yet rather small length of the time series requires to estimate the parameters of the model with few degrees of freedom. Due to the large number of estimations that has to be done (one estimation per occupation per sector) and due to the relative short time series available (14 observed years), coefficients may be biased or estimated with low precision. To gain efficiency and achieve more robust estimates the panel structure of our data could be exploited. In the most general case, the system of N equations of the type 10 could be estimated using the SUR technique. The SUR technique exploits the cross-equation correlations and allows all parameters of each equation to be equation-specific. However, this general specification provides estimates equivalent to the estimates derived from separate OLS regression of equation 10 for each i when each equation has the same set of explanatory variables as is the case in this paper for each equation within industry. In this paper, we use a slightly different approach to account for the cross-equation co-dependence. We first restrict the slope parameters to vary across sectors and occupations but without interaction, and control for occupation and industry fixed effects and year fixed effects. Second, we account for a dynamics correlation across equations in contrast to the contemporaneous correlation assumed in SUR models. The model reads as follows:

$$l_t = \underline{X}_t'(\underline{\gamma} + \underline{D}\underline{\mu}) + \varepsilon_t \tag{11}$$

where $l_t = (l_{1t}, ..., l_{Nt})$, $X_t' = \begin{bmatrix} \underline{X}_{1t}' & 0 \\ & . \\ 0 & \underline{X}_{St}' \end{bmatrix}$ and $\underline{X}_{st}' = \left(\underline{x}_{1t}, ..., \underline{x}_{N_s t}\right)'$ for all equations i so that i belongs to sector s, where N_s is the number of equations that belongs to sector s and S is the total number of sectors. And $\underline{\gamma} = \left(\underline{\gamma}_1, ..., \underline{\gamma}_S\right)'$.
$\underline{D} = \begin{bmatrix} \underline{D}_1' & 0 \\ & . \\ 0 & \underline{D}_S' \end{bmatrix}$ for all t and $\underline{D}_s'$ is a vector containing value 1 if equation i refers to occupation o and 0 otherwise. And $\underline{\mu} = \left(\underline{\mu}_1, ..., \underline{\mu}_O\right)'$ where O is the number of occupations.

The dynamics dependence across occupations and industry is then specified by allowing the error term ε_t in 11 to be correlated with $\Delta\underline{x}_{it}$. A reason for this dynamics dependence is that the error term ε_t in 11 includes factors that are probably taken into account by employers at $t-1$ to determine their optimal choice of inputs for t, so that the usual exogeneity assumptions of $\underline{x}_{it}$, which are required for the consistency of OLS regressions, probably may not hold. In that case, the OLS estimates will be biased (see Griliches and Mairesse (1995)).

To purge the endogeneity in the context of Dynamic OLS (or DOLS) regressions, Mark et al. (2003) proposed a two step estimation procedure. In the first step, we regress i) l_t onto $\Delta \underline{X}_t$ to get $\widehat{l_{ost}} = a_{os} + a_t + \Delta \underline{x}'_{st} \left(\underline{b}_o + \underline{b}_s\right)$ for occupation o in sector s and ii) regress each of the explanatory variables $X_{k,st}$ onto either the vector of first differences in each explanatory variable $\Delta \underline{X}_{st}$, i.e. to obtain the 'ordinary' Dynamic OLS, or $(\Delta \underline{X}_{1t}, ..., \Delta \underline{X}_{St})$, i.e. to obtain the 'system' Dynamic OLS, depending on whether the level of the explanatory variables in sector s has been affected by past variations explanatory variables in sector s only or all sectors. In this paper we choose the second specification as changes in the stock of capital, R&D and value added in one sector will generally contaminate the stock of capital, R&D and value added in other sectors. We therefore have for each explanatory variable k, $\widehat{x}'_{k,st} = c_{k,s} + \sum_{p=1}^{S} \Delta \underline{x}'_{pt} \underline{d}_{k,p}$. Hence,

$$
\begin{aligned}
\underline{x}'_{st} &= \left\langle \widehat{x}'_{1,st}, \widehat{x}'_{2,st}, \widehat{x}'_{k,st} \right\rangle \\
&= \left\langle c_{1,s} + \sum_{p=1}^{S} \Delta \underline{x}'_{pt} \underline{d}_{1,p}, c_{2,s} + \sum_{p=1}^{S} \Delta \underline{x}'_{pt} \underline{d}_{2,p}, c_{3,s} + \sum_{p=1}^{S} \Delta \underline{x}'_{pt} \underline{d}_{3,p} \right\rangle \\
&= \underline{c}_s + \underline{\sum_{p=1}^{S} \Delta \underline{x}'_{pt} \underline{d}_p} = \underline{c}_s + \sum_{p=1}^{S} \underline{\Delta \underline{x}'_{pt} \underline{d}_p}
\end{aligned}
$$

where $\underline{\Delta \underline{x}'_{pt} \underline{d}_p} = \left\langle \Delta \underline{x}'_{pt} \underline{d}_{1,p}, \Delta \underline{x}'_{pt} \underline{d}_{2,p}, \Delta \underline{x}'_{pt} \underline{d}_{3,p} \right\rangle$.

In the second step, we regress the errors $e_{lt} = l_t - \widehat{l_t}$ of the first step regression i) onto the errors $e_{Xt} = X_t - \widehat{X}_t$ of the first step regressions, that is $e_{lt} = e'_{Xt}(\underline{\gamma} + \underline{D\mu}) + \varepsilon_t$, ii) (stacking the sectors and occupations together) to obtain the two-step system dynamics OLS estimator of $\underline{\gamma} = \left(\underline{\gamma}_1, ..., \underline{\gamma}_S\right)'$ and $\underline{\mu} = \left(\underline{\mu}_1, ..., \underline{\mu}_O\right)'$ as:

$$
\left[\frac{\underline{\gamma}}{\underline{\mu}}\right] = \left[\sum_{t=2}^{T} e_{Xt} e'_{Xt}\right]^{-1} \left[\sum_{t=2}^{T} e_{Xt} e_{lt}\right]
$$

Hence, replacing $\widehat{l_{ost}}$ in employment equation for occupation o in sector s, and $\widehat{X}_{st}$ in $e_{l,ost} = e'_{Xst}(\underline{\gamma}_s + \underline{\mu}_o) + \varepsilon_{ost}$ yields:

$$
\begin{aligned}
l_{ost} &= a_{os} + a_t + \Delta \underline{x}'_{st} \left(\underline{b}_o + \underline{b}_s \right) + & (12) \\
& \left(\underline{x}'_{st} - \underline{c}_s - \underline{\sum_p \Delta \underline{x}'_{pt} \underline{d}_p} \right) \left(\underline{\gamma}_s + \underline{\mu}_o \right) + \varepsilon_{ost} \\
&= \underbrace{a_{os} - \underline{c}_s \left(\underline{\gamma}_s + \underline{\mu}_o \right) + a_t} + \underbrace{\underline{x}'_{st} \left(\underline{\gamma}_s + \underline{\mu}_o \right)} & (13) \\
& \underbrace{+ \Delta \underline{x}'_{st} \left(\underline{b}_o + \underline{b}_s \right) - \underline{\Delta \underline{x}'_{st} \underline{d}_s} \left(\underline{\gamma}_s + \underline{\mu}_o \right)} - \underbrace{\left(\underline{\gamma}_s + \underline{\mu}_o \right) \sum_{p \neq s} \underline{\Delta \underline{x}'_{pt} \underline{d}_p}} + \varepsilon_{ost}
\end{aligned}
$$

where a_{os} is a occupation×sector fixed effect, $\underline{c}_s \underline{\gamma}_s$ is a sector fixed effect and a_t a year fixed effect. The occupation specific vector of parameters $\underline{b}_o$ indicates the effect of a 1% increase in the respective explanatory variables between $t-1$ and t on the level of employment in occupation o, similarly, the sector specific vector of parameters $\underline{b}_s$ indicates the effect of a 1% increase in the respective explanatory variables of sector s between $t-1$ and t on the level of employment in sector s. $\underline{\Delta \underline{x}'_{st} \underline{d}_s} \left(\underline{\gamma}_s + \underline{\mu}_o \right)$ indicates the effect of a 1% increase in the respective explanatory variables of sector p between $t-1$ and t on the level of employment in occupation o in sector s.

In equation 13, the first two sets of terms depict the long-run structure of employment. The first term includes occupation×sector fixed effects, sector and occupation fixed effects and year fixed effects. The second term indicates the long run relationship between value added, capital and R&D and employment with sector-specific $\underline{\gamma}_s$ and occupation-specific $\underline{\mu}_o$ parameters. $\underline{\gamma}_s + \underline{\mu}_o$ indicates the percentage change in employment in occupation o in sector s to a 1 percent change in the corresponding explanatory variable.

The third and fourth sets of terms capture the dynamics relationship between the level of employment in occupation o in sector s at time t and changes in the explanatory variables. The third term sizes the effect of changes in the explanatory variables on employment intrasectoral whereas the fourth term indicates this effect intersectoral. The dynamics intrasectoral has occupation and sector specific slopes whereas the intersectoral dynamics has only a sector specific slope. Similarly, a test for the block-significance of $\underline{d}_p$ for sector s with $p \neq s$ would indicate whether the dynamics of the explanatory variables occurs merely within sector of whether changes in value-added, R&D or capital stock in a particular sector between $t-1$ and t has an impact on the level of these variables in other sectors at time t.

4 Results

4.1 Estimates

Results of the system dynamics estimation procedure depicted previously are reported in Table 2. The first block of parameters refer to the long-run elasticities of employment series with respect to the value added, capital and R&D. For each explanatory variable, the F-statistics reported in Table 2 indicate that these elasticities are block-significant. The elasticity with respect to value added is the largest in the building industry[3] $0.8 + 3.6 = 4.4$ (significant at 5%) and the smallest in Governance and education, -3.1. In contrast, the employment elasticity with respect to capital is the largest in Governance and education 6.6 (significant at 1%) and the smallest in Agricultural sector -2.5 (significant at 5%). The elasticity with respect to R&D is the largest in the trade sector, 0.5 (not significant) and smallest in the Paper, plastic, rubber and other industries, -1.6 (significant at 1%).

Table 2 reports only those occupation-specific elasticity parameters that are significant at 1%. However, we also report the number occupations for which the elasticity parameter is significant at 5% for each of the three explanatory variables. It is interesting to note that high-skill occupations, in general, have a negative and significant elasticity with respect to value added but a large and significant elasticity with respect to R&D. Output expansion in a sector leads to a decrease in employment in high-skill occupations within that sector. However, this effect can be partly or fully compensated by the complementarity of high-skilled workers with new technology as indicated by the positive elasticities of employment in high-skill occupations with respect to R&D. Another interesting result to note is that in particular the intermediate-skill occupations have a positive and significant elasticity with respect to capital.

In addition, we tested for the significance of the short-run dynamics parameters. We first tested, by means of a F-test, whether the vector of sector-specific parameters $\underline{b}_s$ is significantly different from $\underline{0}$, that is we tested whether changes in value added, capital and R&D between t and $t-1$ in sector s affect employment level at time t in sector s. The F-test statistic turns out to be equal to 17.9 which is significant at 1%. We also tested whether vector of occupation-specific parameters $\underline{b}_o$ is significantly different from $\underline{0}$, that is we tested whether changes in value added, capital and R&D between t and $t-1$ in sector s affect employment level at time t in occupation o. The F-test statistic turns out to be equal to 2.8 which is also significant at 1%. Next we tested whether the vector of sector-specific parameters $\underline{d}_p$ is significantly different from $\underline{0}$, that is whether the employment dynamics in sector s is in part due to changes in value-added, capital stock and R&D that occur in other sectors. The test-statistics are equal

[3] The coefficients are relative to the reference sector×occupation, i.e. unskilled occupation in the Agricultural sector.

to 434.1, 229.2 and 308.45 for value-added, capital stock and R&D respectively and all significant at the 1% level.

We conclude that short run intersectoral dynamics play a significant part in the occupational structure of the various sectors. To size the share of the intersectoral dynamics, we first derived the ex post prediction of the occupational employment series using the full model as depicted in equation 13 and then shutting down the intersectoral dynamics, i.e. setting $\left(\underline{\gamma}_s + \underline{\mu}_o\right) \sum_{p \neq s} \underline{\Delta \underline{x}'_{pt} \underline{d}_p} = 0$. This allows to derive the share of our model's prediction due to intersectoral dynamics. These shares are reported in Table 3. On average, the intersectoral dynamics account for 20% of our predicted the occupational employment series. Although, large variations are observed across sectors. While our predicted employment series in the Metal industry, Paper, plastic rubber and other industries, Energy, Building trade and Hotel and catering are merely due to intrasectoral dynamics (share of intersectoral dynamics is less than 10%), our predicted occupational employment series in the Agricultural, Chemical, Transport, Banking and insurance and Governance and education sectors are to a large extent affected by intersectoral dynamics, 61%, 36%, 30%, 25% and 34% respectively.

4.2 Illustration

From Table 2 it follows that employment in the Chemical industry significantly increases due to investments in capital. The opposite holds for investments in R&D in the Transport sector. However, for each of the occupational classes in these sectors the long-run employment effect may be different. We illustrate this by presenting the changes in employment for three occupational classes within the Chemical as well as the Transport sector between 1988 and 2003. The actual and predicted employment series of three occupational classes in both sectors of industry are shown in six figures. Furthermore, we distinguish between employment predictions with and without intersectoral dynamics. The difference between both predictions indicates the contribution of intersectoral dynamics conditional on the contribution of intrasectoral dynamics. This contribution is virtually insignificant when intra and intersectoral predictions are highly correlated and explain the same share of the employment dynamics. For the 195 combinations of sector of industry and occupational class about 80% of the variance of the employment predictions comes from the intrasectoral dynamics. Moreover, there is imperfect correlation between the predictions of the full model and the predictions without intersectoral dynamics, about 0.86 in average, indicating a significant marginal relevance of intersectoral dynamics.

Figures 1, 2 and 3 show the actual and predicted employment in the Chemical industry for the technical occupations at three skill levels respectively. For the low-skill technical occupations in the Chemical industry it turns out that employment has diminished over time. The change in employment is better predicted when intersectoral dynamics are included in the estimations. The intersectoral dynamics play an important role for this occupational class as indicated by its relatively large share in explaining the predictions of the full model, i.e. 0.44, and the relatively low correlation between the total and intrasectoral employment predictions, i.e. 0.74. This implies that the factor input of low-skill technical occupations in the Chemical industry is significantly related to the capital and R&D investments in other sectors of industry.

Also, for the intermediate-skill technical occupations in the Chemical industry the employment trend is downwards, although less strongly than for the low-skill technical occupations. The change in employment seems to be only slightly better predicted when intersectoral dynamics are included in the estimations. This can be seen from the high correlation between the predictions of the full model and the model without intersectoral dynamics, i.e. 0.92 and the low share of the total predictions due to the intersectoral dynamics, i.e. 0.15. For the high-skill profesional technical occupations in the Chemical industry the time series may be too short and the sample variance is too large to conclude whether employment is decreasing or constant. Moreover, there too, no clear advantage of including intersectoral dynamics in the prediction of employment can be seen. This is confirmed by the large correlation between the employment predictions with and without intersectoral dynamics, i.e. 0.87. For the Chemical industry total employment has decreased since 1988. It seems that the average level of required technical qualifications (measured by the job level of technical occupations) has risen in the Chemical industry from 1988 to 2003, since the share of high-skill professional technical occupations increased at the expense of the low-skill technical occupations.

For the Transport sector we show in Figures 4, 5 and 6, the change of employment for three different high-skill professional occupational classes respectively. In two out of three of these occupational classes employment has increased since 1988. For the high-skill professional technical occupations in the Transport sector there is no clear employment trend. Also for this occupations sample variance seems to be rather large. For this combination of sector of industry and occupational class the intersectoral dynamics are very important in the prediction of employment, since they account for more than 85% of the full model predictions. Moreover, the correlation between both the full model predictions and the predictions without intersectoral dynamics is rather low, i.e. 0.37. Therefore, including intersectoral dynamics in the estimation model improves significantly the employment prediction for the high-skill professional technical occupations. On the contrary, the intersectoral dynamics do not improve the employment predictions for the transport and the economic and commercial occupations at the high-skill professional level. The correlation between both employment predictions is close to unity and the share of the predictions of the full model due to intersectoral dynamics is nearly 0.

It follows that the predictions of employment changes for the six occupational classes discussed above is very well in line with the actual employment changes. We can conclude that the performance of the estimation model is rather good in these cases.

5 Conclusion

In this paper, we develop a new model to explain the occupational structure of sectors of industry. We estimate the structural parameters of the model for the period between 1988 and 2003 using system dynamics OLS techniques to account for the employment dynamics dependence across occupations and sectors of industry. The employment series by occupation and sector have both a long run relationship with levels of value added, capital and R&D, reflecting the production technology specific to each sector, and a short-run relationship with changes in value added, capital and R&D. The short run dynamics can further be decomposed into intra and intersectoral dynamics. The intrasectoral dynamics indicate that changes in the explanatory variables in a sector affect occupational employment in that sector whereas the intersectoral dynamics indicates that changes in the explanatory variables in a sector affect occupational employment in other sectors.

We find that both the long run and short run relationships explain a significant part of employment by occupation and sector of industry. Moreover, employment by occupation and sector is significantly affected by not only the intrasectoral dynamics but also by the intersectoral dynamics. In addition, the results of the paper indicate that high-skill occupations have a negative and significant elasticity with respect to value added but a large and significant elasticity with respect to R&D. Output expansion in a sector level to a decrease in employment in high-skilled occupations within that sector. However, this effect can be partly or fully compensated by the complementarity of high-skilled workers with new technology as indicated by the positive elasticities of employment in high-skilled occupations with respect to R&D. Moreover, in particular the intermediate-skill occupations have a positive and significant elasticity with respect to capital.

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Table 1: Number of sectors and occupations for which the series are not stationary (ADF statistic) .

ADF-test[a]	Number of occupations	Employment[b] I(0)	I(1)	Variables Capital I(1)	R&D I(1)	Value added I(1)	Cointegrated[c]
Sectors							
1	7	0	7	Yes	Yes	Yes	4
2	8	0	8	Yes	Yes	Yes	7
3	11	3	8	Yes	Yes	Yes	11
4	11	2	9	Yes	Yes	Yes	11
5	10	2	8	Yes	Yes	Yes	10
6	7	5	2	Yes	Yes	Yes	7
7	10	3	7	Yes	Yes	Yes	10
8	18	0	18	Yes	Yes	Yes	17
9	12	3	9	Yes	Yes	Yes	12
10	7	2	5	Yes	Yes	Yes	7
11	29	2	27	Yes	Yes	Yes	29
12	30	0	30	Yes	Yes	Yes	30
13	35	1	34	Yes	Yes	Yes	30
Total	195	23	172	13	13	13	185
%		12	88	100	100	100	95

[a] Augmented Dickey-Fuller test with drift.

[b] The number of series with p-value larger than 5% are reported in column I(0) and number of series with p_value smaller than 5% are reported in column I(1).

[c]The number of occupations for which equation 8 depicts longrun relationship, i.e. for which the ADF statistic test on the errors of the OLS regression of equation 8 is significant at 5%.

Table 2: Long-run structural parameter estimates by sector and occupation (N=2925).

Variables:		Value added				Capital				R&D		
Sectors: γ_s		Coef		Std		Coef		Std		Coef		Std
Reference: sector 1 occupation 1		0.774		0.8706		−2.491	$*$	1.0981		0.064		0.4061
2		−0.849		1.0293		0.823		1.4697		0.211		0.7166
3		−1.299		0.9488		2.277	$*$	1.1350		−0.493		0.4417
4		−1.295		1.0028		1.472		1.2427		−0.113		0.4354
5		−0.272		1.1232		4.044	$**$	1.3380		−1.691	$**$	0.5445
6		−1.597		0.9786		2.390	$*$	1.1926		0.554		0.4576
7		3.606	$*$	1.5057		−3.313		1.9750		−0.401		0.4140
8		−1.828		1.0973		2.801	$*$	1.1597		0.583		0.5259
9		−0.304		0.8662		−0.136		1.2738		−1.079	$*$	0.5333
10		1.949		1.0353		0.209		1.1916		−0.390		0.4067
11		−0.948		0.9607		2.006		1.1003		−0.257		0.4394
12		−0.220		0.9366		1.608		1.2098		−0.994		0.5218
13		−3.939	$**$	1.0353		9.107	$**$	1.5458		−0.062		0.4852
F-test(13,2886)[a]		7.290	$**$			7.400	$**$			5.260	$**$	
Occupations with $\mu_o \neq 0$ at 1%												
	4	1.854	$**$	0.6551	13	1.575	$**$	0.5161	4	0.402	$**$	0.2363
	6	−1.245	$**$	0.3745	16	1.620	$**$	0.5154	6	0.449	$**$	0.1410
	18	−1.022	$**$	0.3657	21	2.454	$**$	0.5269	9	0.273	$**$	0.0912
	21	−3.233	$**$	0.9885					29	0.258	$**$	0.0912
	24	3.269	$**$	1.2758					34	0.706	$**$	0.263
	34	−2.245	$**$	0.6308					38	0.567	$**$	0.1983
	41	−1.701	$**$	0.6423					40	0.238	$**$	0.0971
	42	−2.573	$**$	0.9885					41	0.429	$**$	0.1081
									42	1.304	$**$	0.5048
Number of o with $\mu_o \neq 0$ at 5%		13				11				10		

[a]For each of the three variables, we F-test the null hypopthesis of equal coefficients in all sectors.

$*$sig at 5%

$**$sig at 1%

Table 3: Average share of short run intersectoral dynamics in the model's predictions of employment series by sector and occupation.

Sectors	Share of inter-sector dynamics	Correlation[a]
1	0.61	0.49
2	0.13	0.93
3	0.36	0.79
4	0.02	0.99
5	0.04	0.98
6	0.04	0.98
7	0.04	0.98
8	0.17	0.88
9	0.30	0.78
10	0.25	0.83
11	0.08	0.96
12	0.18	0.89
13	0.34	0.70
Total	0.20	0.86

[a] Correlation between the predictions of the full model and the predictions without intersectoral dynamics

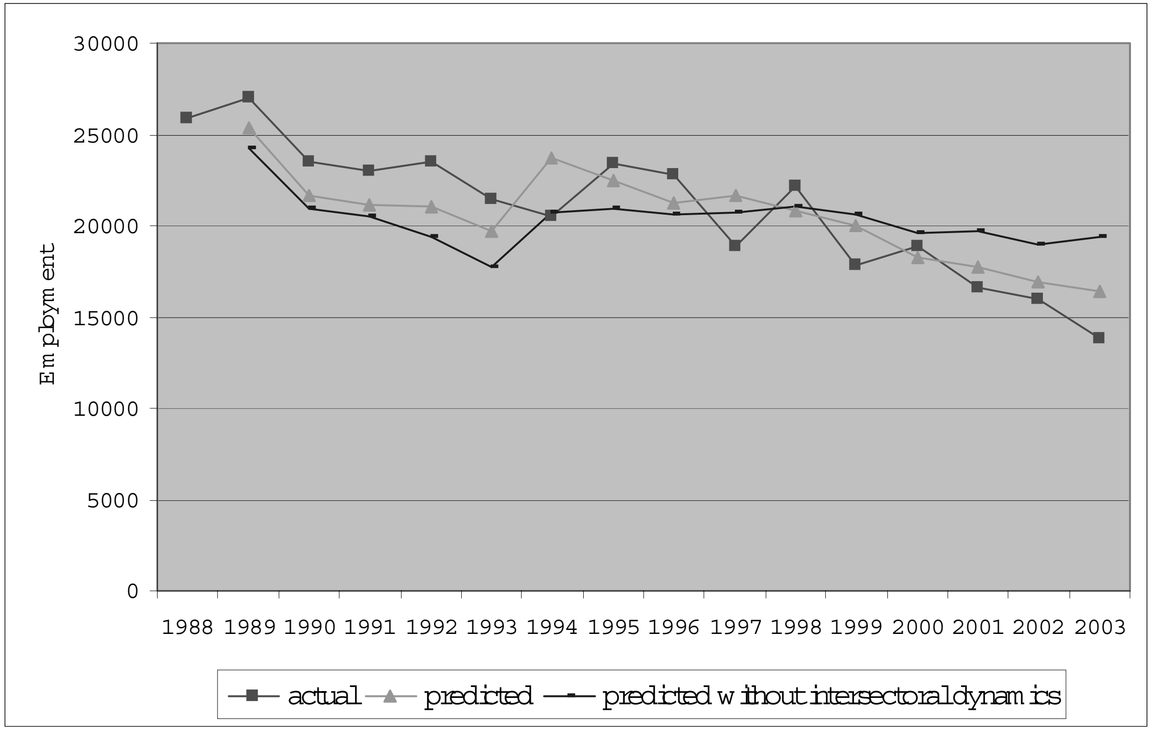

Figure 1: Employment dynamics of low-skill technical occupations in Chemical industry.

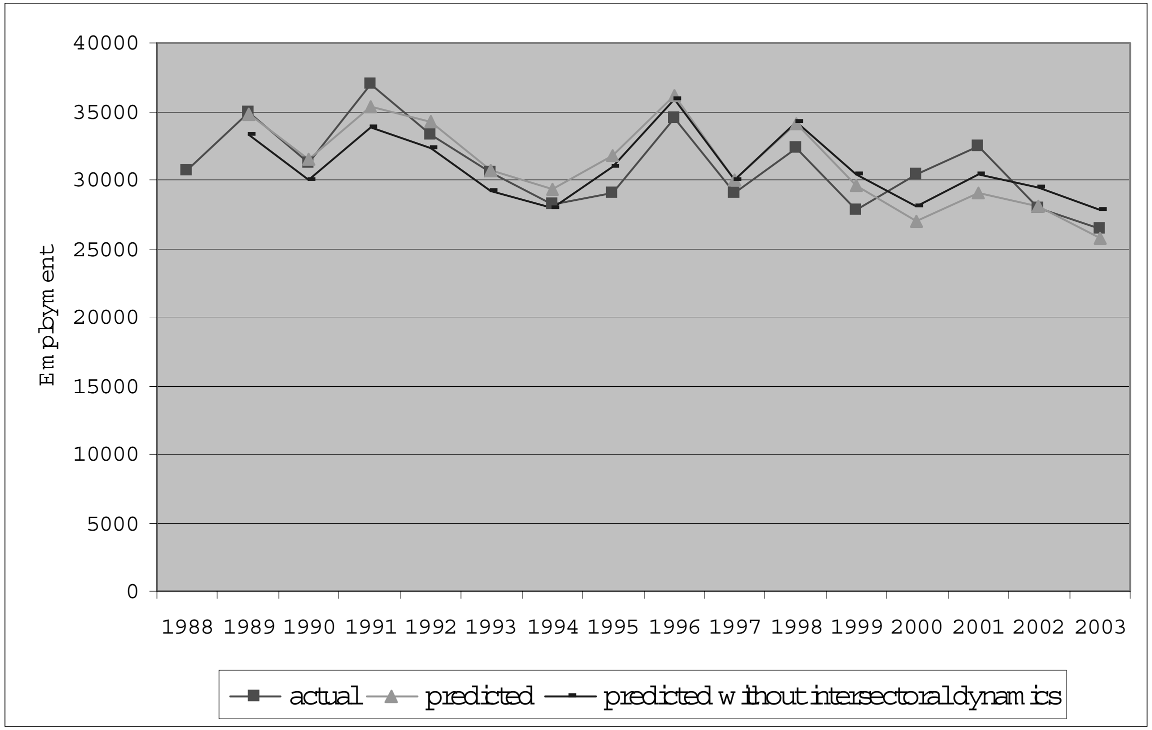

Figure 2: Employment dynamics of intermediate-skill technical occupations in Chemical industry.

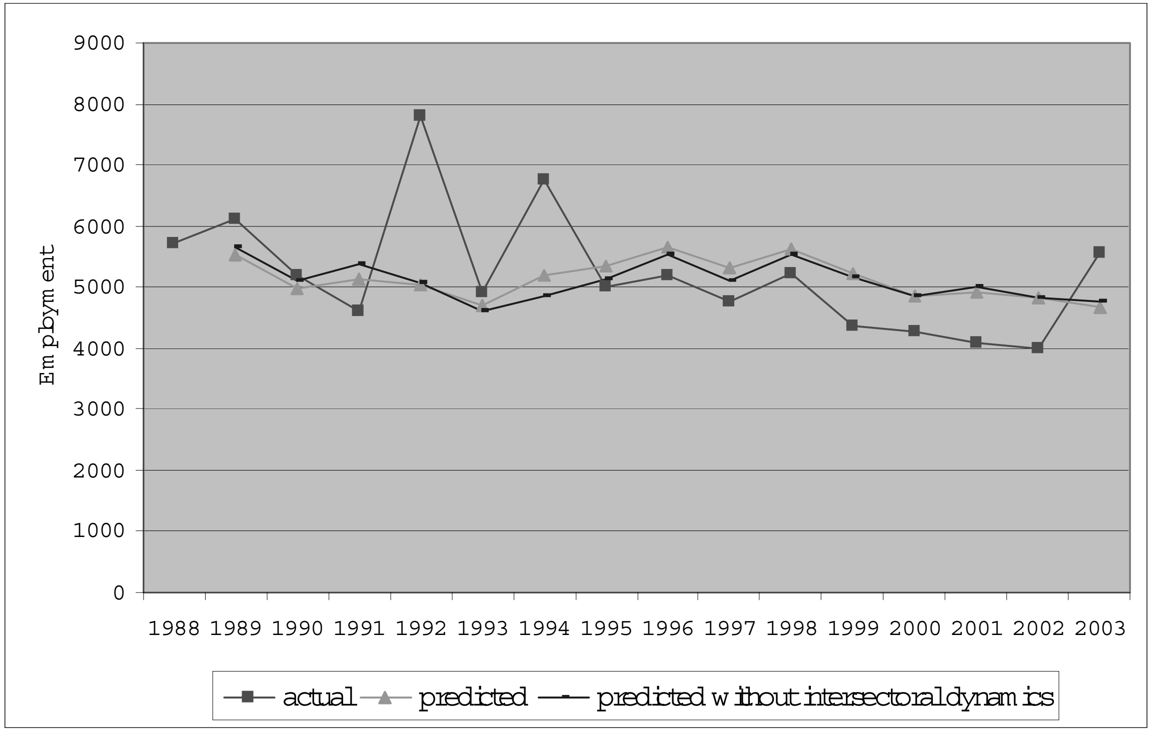

Figure 3: Employment dynamics of high-skill technical occupations in Chemical industry.

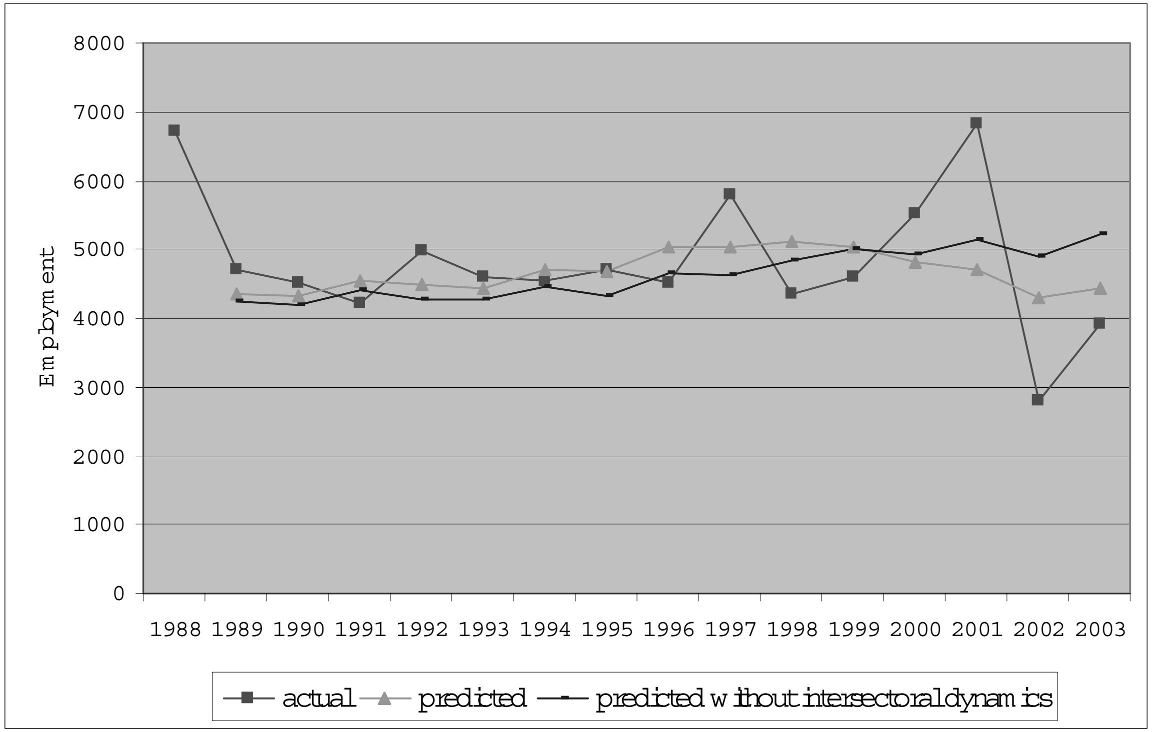

Figure 4: Employment dynamics of high-skill professional technical occupations in Transport sector.

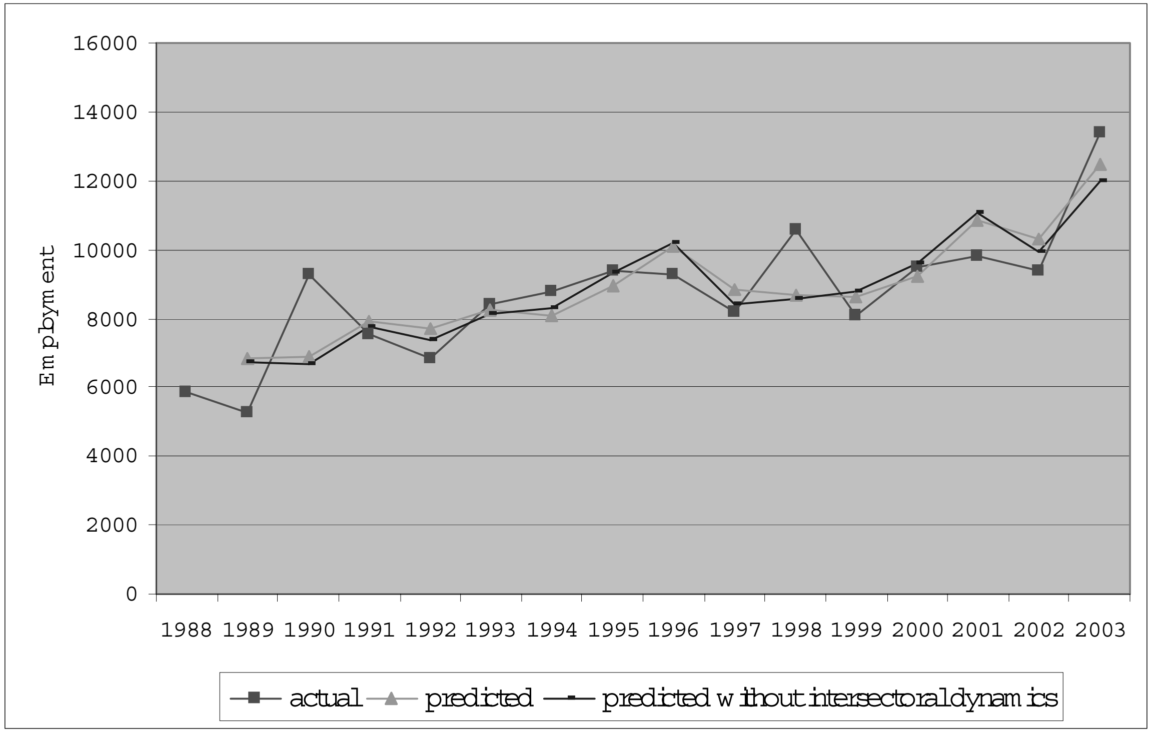

Figure 5: Employment dynamics of high-skill professional occupations in Transport sector.

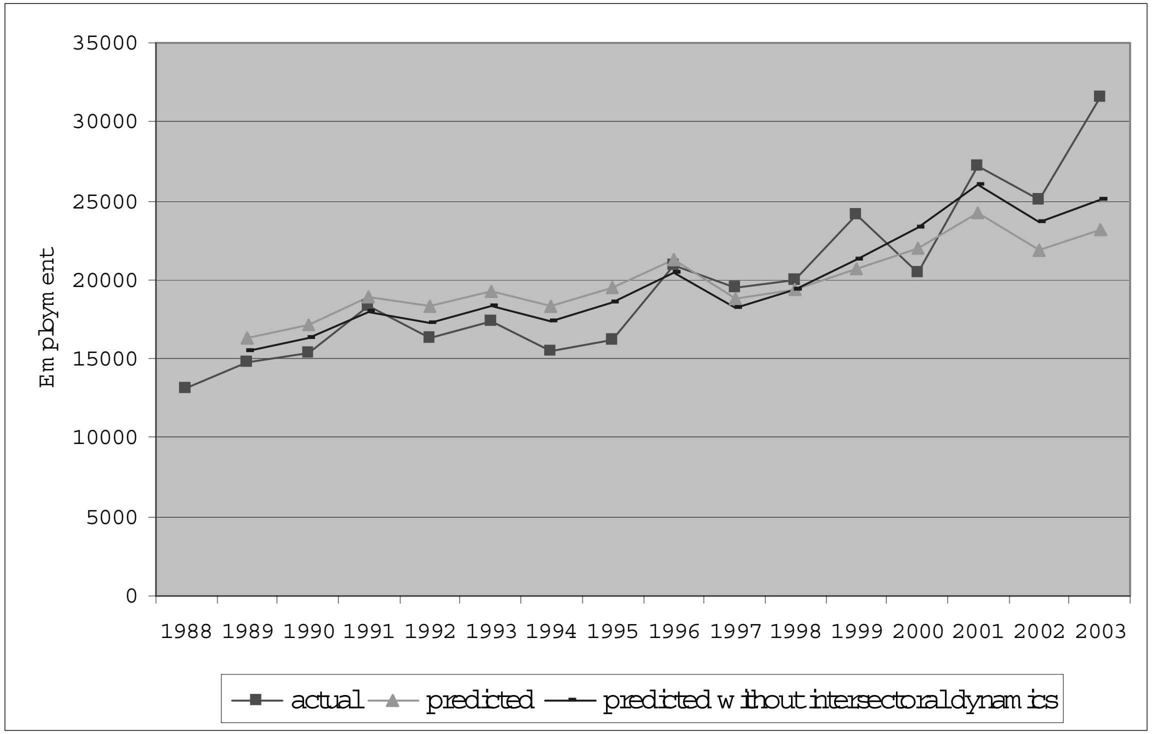

Figure 6: Employment dynamics of high-skill professional commercial and administrative occupations in Transport sector.

1	Agriculture
2	Food industry
3	Chemical
4	Metal industry and electronics
5	Paper, plastic, rubber and other industries
6	Energy
7	Building trade
8	Trade
9	Transport
10	Banking and insurance
11	Hotel and catering industry, commercial services
12	Health care and other public services
13	Governance and education

1 Unskilled occupations

2-11 Low-skill occupations
2 General
3 Sports instructors
4 Agricultural
5 Mathematics and natural sciences
6 Technical
7 Transport
8 Medical and health-related
9 Clerical and commercial
10 Security
11 Home economics and service trades

12-22 Intermediate-skill occupations
12 Instructors in transport and sports
13 Agricultural
14 Mathematics and natural sciences
15 Technical
16 Transport
17 Medical and health-related
18 Clerical and commercial
19 Legal, public administration and security
20 Humanities, documentation and fine arts
21 Social and behavioural
22 Home economics and service trades

23-34 High-skill professional occupations
23 Teachers and educationalists
24 Agricultural
25 Mathematics and natural sciences
26 Technical
27 Transport
28 Medical and health-related
29 Economic and commercial
30 Legal, public administration and security
31 Humanities, documentation and fine arts
32 Social and behavioural
33 Home economics
34 Managers

35-43 High-skill academic occupations
35 Teachers and educationalists
36 Agricultural
37 Mathematics and science
38 Technical
39 Medical and health-related
40 Economic and commercial
41 Legal, public administration and security
42 Humanities, social and behavioural
43 Managers